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Intelligent Model Library for Nonferrous Metal Industry: Construction Method and Application

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Abstract: The nonferrous metal industry is the foundation of China's real economy and plays a vital role in the national economy and defense construction. Industrial software is crucial for the high-quality development of the nonferrous metal industry and is associated with the in-depth implementation of national software development strategies. Currently, the development of industrial software in the nonferrous metal industry is significantly restricted by a lack of knowledge models. Hence, we propose a method to construct an intelligent model library for the nonferrous metal industry. Considering meta-model-driven engineering, we defined a nonferrous metallurgical meta-model and its attributes and proposed a meta-modeling method based on the MODELING architecture. In addition, we designed an overall architecture for an intelligent model library based on the industrial Internet, an agile model development environment integrating multiple languages, and a meta-model encapsulation system based on multi-scenario black-box reuse. Moreover, a meta-model full lifecycle management platform was constructed using a five-layer, two-dimensional classification standard, and a domain knowledge graph. An intelligent model library for the nonferrous metal industry was developed based on the long-term accumulation of nonferrous metallurgy process mechanisms, operating experience, and intelligent methods. The role of the intelligent model library in improving the intelligence level in engineering applications was presented through the application of two typical nonferrous metallurgical scenarios. The intelligent model library of the nonferrous metal industry serves as a vital source of core knowledge for advancing industrial software, and its role is fundamental in driving smart manufacturing and strengthening the nonferrous metal industry as a whole.
Keywords: nonferrous metal industry; industrial software; meta-model; intelligent model library; industrial Internet

1 Introduction

The nonferrous metal industry is the pillar industry of the national economy, the foundation for the development of the real economy, and an important source of manufacturing power [1]. Over the past 40 years of reform and opening-up, China has witnessed remarkable advancements in nonferrous metal production technology, equipment, and automation levels, leading to the establishment of a comprehensive and modern nonferrous metallurgical industrial system in the country [2]. The production and consumption of nonferrous metals in China have been

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ranked first worldwide for many years [3]. For example, the output of ten commonly used nonferrous metals accounts for more than 50% of the world's nonferrous metal production [4]. Despite the significant advancements made in China's nonferrous metal industry, a noticeable gap between China and leading nonferrous metal powerhouses remains. The high-quality development of the nonferrous metal industry faces challenges such as high emissions, high energy consumption, and serious labor dependence. Hence, there is an urgent need to promote the deep integration of informatization and industrialization and promote green, intelligent, and efficient production through intelligent manufacturing [5].

As a product of the softwareization of industrial technology, industrial software is a key support for virtual manufacturing, digital process design, and production optimization control. It is also a core element of intelligent manufacturing in the nonferrous metal industry [6,7]. Industrial software, an urgent issue in China's current scientific and technological research, is related to the long-term development of industrial systems [8]; it has strong industrial attributes and is a coded expression of industrial knowledge. Software is the application carrier, and the model is the core that embodies the technological capabilities of industrial software. In the nonferrous metal industry, the nonferrous metallurgical model encapsulates process mechanisms, best practices, and other aspects of the production process, serving as the bottom and core support for industrial software. In summary, it provides a technical knowledge base for industry intelligence and promotes the intelligent transformation of the nonferrous metal industry [9].

Considerable research has been conducted on various aspects of the nonferrous metal production process, forming a series of knowledge models. For example, a hybrid nonlinear model predictive controller was proposed for a mining grinding system to ensure stable control of the grinding circuit under external interference [10]. A method for identifying antimony flotation conditions based on the combination of multiple information fusion and extension theory was proposed, achieving accurate identification of antimony flotation conditions [11]. An intelligent integrated modeling and description method was proposed for nonferrous metallurgical processes, and optimization methods were explored in conjunction with multiple types of nonferrous metallurgical engineering problems [12]. Moreover, a process monitoring method based on label propagation dictionary learning was studied for complex production processes in nonferrous metallurgy, and its effectiveness was verified using aluminum electrolysis [13]. To address the dynamic uncertainty characteristics of nonferrous metallurgical processes, probability, fuzzy, and interval uncertainty optimization methods were proposed for typical scenarios [14]. Dynamic optimization control methods were adopted to effectively improve the control accuracy of titanium processing and forming [15].

While various models exist for nonferrous metal production, such as process modeling and operation optimization, many of these models are tailored for specific scenarios; this high level of integration makes them challenging to apply in different scenarios and contexts. The development of relevant models is mostly conducted separately, without aggregating and managing model resources on a unified standard platform, resulting in large differences and poor compatibility among models. The fragmentation and dispersion of nonferrous metallurgical models make it difficult to effectively support industrial software development [16]. Therefore, the shortage and uneven quality of nonferrous metallurgical models have significantly hindered industrial software development. To promote the high-quality development of the nonferrous metal industry, it is crucial to consolidate industry knowledge and create universal and highly compatible models. The construction of standardized and scalable aggregation management platforms for the entire industry is vital. By integrating advantageous resources through the model library, a new ecosystem of resource enrichment and collaborative evolution can be fostered. Moreover, it is important to explore effective solutions for addressing the challenge of insufficient core knowledge in industrial software and promote the overall development of industrial software in the nonferrous metal industry.

This study takes the nonferrous metallurgy universal model and aggregation management platform as starting points and systematically analyzes the construction method of the nonferrous metal industry model library. It summarizes the requirements for constructing a nonferrous metal intelligent model library, defines the nonferrous metallurgical meta-model and meta-modeling paradigm, and proposes an intelligent model library construction technology based on the industrial Internet of Things (IIoT). Based on industrial knowledge, a nonferrous metal intelligent model library is constructed, and the application efficiency of the model library is verified through typical scenarios in nonferrous metallurgy. Finally, the future research direction of the model library is explored to provide inspiration and reference for the intelligent development of the nonferrous metal industry.

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2 Demand for constructing nonferrous metal industry intelligent model library

2.1 Macro architecture of nonferrous metals industry model library

Considering the current state of the nonferrous metal industry, existing model libraries mostly exist as offline resources with limited contents and incomplete categories, which are difficult to access and use. The model resources are disconnected from actual applications, making it difficult to integrate them into the development trend of intelligent manufacturing and networked collaboration and insufficient to support the formation of model development/application/service formats.

The IIoT is a product of the deep integration of the latest generation of information technology and modern industrial technology. It is an important carrier for the digitization, networking, and intelligence of manufacturing, becoming a strategic vantage point in the new era of industrial competition [17]. At the national planning level, it is necessary to accelerate the construction of a strong manufacturing country; this involves accelerating the development of advanced manufacturing and promoting the deep integration of the Internet, big data, artificial intelligence (AI), and the real economy [18]. As a key infrastructure in intelligent manufacturing, IIoT can help the nonferrous metal industry achieve intelligent production, networked collaboration, and service-oriented transformation.

The infrastructure-as-a-service (IaaS) layer in the IIoT provides a strong infrastructure and massive data for the nonferrous metal industry intelligent model library. The open cloud operating system in the platform-as-a-service (PaaS) layer provides scalable and compatible service support, and the application construction method of industrial applications (APP) in the software as a service (SaaS) layer provides a convenient and lightweight method for applications in different scenarios [19]. Therefore, the IIoT provides carrier support and application channels for the model library, and the platform’s resource aggregation and sharing capabilities promote the application of the model library.

In the new era and stage, understanding the direction of intelligent manufacturing and building an intelligent model library for the nonferrous metal industry based on the IIoT will accelerate the development of industrial intelligence, form new driving forces for the transformation and upgradation of the nonferrous metal industry, effectively alleviate the problem of the lack of core knowledge models faced by domestic industrial software in the nonferrous metal industry, and build a solid foundation for the development of intelligent models and industrial software in the nonferrous metal industry.

2.2 Technical requirements for constructing a nonferrous metals industry model library

2.2.1 Describing the phase-field coupling characterization of the nonferrous metallurgy process is difficult, and the model is highly integrated and has poor versatility; therefore, it is necessary to define a meta-model with moderate granularity and a standardized modeling paradigm.

Nonferrous metallurgy represents a typical long-process industrial scenario characterized by complex physical and chemical reactions during production. The process involves complex interactions among multiple phases, including gas, liquid, and solid phases, and exhibits electric–magnetic–thermal–flow–force–concentration multi-field coupling phenomena. This usually requires multiple processes and various pieces of equipment to collaborate, with strong process correlation and data complexity. The corresponding models contain multiple parameters and the models are coupled with each other [20]. Nonferrous metallurgy practitioners face challenges in encoding and developing complex models, whereas software developers face difficulties in understanding the coupled relationship between industry knowledge and codes. Hence, a serious industry knowledge barrier has led to difficulties in developing nonferrous metallurgy models. In the traditional model-development mode, developers encapsulate multiple complex functions to form higher-level coarse-grained models in pursuit of integration. The excessive integration of the original model and the lack of independent disassembly necessitate significant modifications or complete recoding when calling a specific function for a new scenario, resulting in duplicate model development and low application efficiency.

To solve the problems of model coupling, development difficulty, high integration, and low universality, models should be decoupled and split into moderately granular and generalized basic meta-models to represent industry knowledge. This can significantly reduce the development and application difficulties, promote the deposition and reuse of industrial knowledge, and guide the healthy development of industry model libraries.

2.2.2 Models suffer from poor compatibility and reusability owing to diverse compilation environments. Hence, an agile development environment supporting multiple languages is required to facilitate model integration and enhance efficiency.

From the perspective of a meta-model developer, the current model development is often fragmented owing to differences in knowledge and skills among developers who may use various programming languages such as Python, C++, Java, and others. Existing single development environments struggle to accommodate the diverse needs of the model development process, resulting in isolated language models with poor compatibility and collaboration challenges. Hence, a model development environment must enable collaborative development across multiple languages. From the perspective of a meta-model user, multiple meta-models should be combined according to the actual requirements to obtain a model with specific complex functions. However, meta-model integrators are mostly professionals in the nonferrous metal industry who have rich domain knowledge while lacking proficient programming skills, making it difficult to inherit and derive meta-model codes from scratch to form complex models in a short period of time.

Graphical and configuration-based development environments are highly suited for agile use by personnel. These environments allow users to visually combine multiple meta-models based on logical relationships, facilitating the creation of complex function models without the need for coding. This significantly reduces the model development threshold and improves overall efficiency [21].

2.2.3 The current model management suffers from low efficiency and challenges in promotion and application. Hence, a comprehensive lifecycle management platform covering classification management, review, and evaluation, and a precise search is required.

The nonferrous metal industry includes a wide range of categories, long production processes, diverse process types, and highly coupled process units with complex reaction mechanisms. As the basic carriers of knowledge in the nonferrous metal industry, meta-models are numerous, diverse, and strongly correlated [22]. As the number and variety of developed meta-models increase, without effective organizational management, the meta-models may become fragmented and difficult to navigate, resembling “scattered sand.” Users often face challenges in quickly locating the appropriate meta-model when developing services that require specific functions. This leads to underutilization of many meta-models; as a result, the full potential of the model library remains unused.

Therefore, it is crucial to focus on the entire lifecycle of meta-models and build a comprehensive management platform that integrates classification management, review, evaluation, and accurate search functionalities to efficiently manage massive model resources and fully promote the practical application and value presentation of the model library.

3 Construction technology of nonferrous metal industry meta-models

3.1 Definition and characteristics of meta-models

Nonferrous metallurgy models are mathematical (software) expressions of the quantitative or qualitative relationships between variables in a nonferrous metallurgy system (object), including mechanism models, data models, knowledge models, and AI methods. The purpose of this study is to describe the dynamics of a nonferrous metallurgy system (object) and support the process design, operation control, and decision optimization in the nonferrous metal industry. Decoupling the model and breaking it down into multiple independent model units, using meta-models with moderate granularity and universalization to represent industry knowledge, can significantly reduce the threshold for model development and application and promote the development level of the industry model library.

Meta-models are model units with independent decision-making functions that cannot be further decomposed; they are the basic elements for creating models in specific domains (i.e., the “models” of models). Independent units with complex functions are abstract representations of code, and high-level functional units are composed of multiple basic functions. Models are defined jointly by multiple meta-models and are advanced combinations of meta-models that are closer to application services and have richer functionalities than meta-models. Meta-models can be combined using parallel integration, weighted integration, serial integration, nested integration, structural network integration, and partial substitution integration. A single meta-model can be used with multiple models, and a single model can be associated with multiple meta-models. Meta-model-driven engineering (MDE) is generally divided into three layers, from bottom to top: code block layer M0, meta-model layer M1, and model layer M2 (Fig. 1).

Meta-models are object-oriented and structure codes related to specific functionalities as a unified entity; they

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provide a higher-level representation of systems, enabling them to closely resemble the natural operational patterns of real-world entities. As a fine-grained representation of models, meta-models are essentially forms of models with the same scope of application, structural form, and method set. By abstracting the code and decoupling the models, industrial knowledge can be precipitated and solidified with moderate complexity. A triple can represent each meta-model; a meta-model is a model unit that contains this triple and cannot be further divided, whereas a model can be described as an organic combination of meta-models.

Meta-models are independent, intelligent units with complex functions utilized in meta-model-driven engineering, software development, and IIoT applications; they possess the following distinct key characteristics: (1) Reusability: Meta-models are built as standardized, generalized, and reusable components that remain consistent across different applications. Reusable meta-models have good adaptability, improving model development and application efficiency, reducing development costs, and improving system maintainability. (2) Interoperability: Meta-models developed in different programming languages and development environments can connect and exchange data without obstacles, thus forming a model service through the interoperability of multiple meta-models. (3) Cross-platform: Meta-models can be directly executed in different language environments, operating systems, hardware configurations, and IIoT platforms without modifying the original files or codes. Compared with native development, service development based on cross-platform meta-models has advantages such as low cost, shorter development cycles, and reduced complexity.

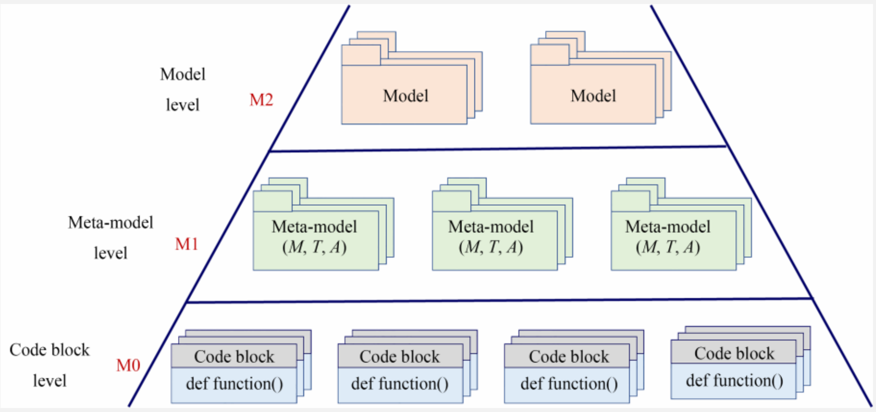

Fig. 1. Three-layer architecture of meta-model driven engineering.

Note: *M* is the prototype object of meta-model; *T* is the data type of the input, output, and formal parameter sets of meta-model; *A* is the functional attribute of meta-model.

3.2 Modeling paradigm of nonferrous metal industry meta-model

The highly specialized and interdisciplinary nature of nonferrous metallurgical knowledge can lead to significant differences in the understanding and description approaches used by experts in different domains, resulting in inconsistent quality of meta-models. Hence, a process-oriented and standardized meta-modeling paradigm is required as a methodological guide to ensure consistency and improve the efficiency and quality of meta-modeling. This study proposes a meta-modeling approach for nonferrous metallurgy based on a MODELING framework, employing hierarchical development and iterative optimization to construct meta-models with abstraction objects, concrete descriptions, and software applications.

The MODELING method for meta-models of nonferrous metallurgy includes modeling objects, functional definitions, expression forms, logical interfaces, standardized coding, and iterative optimization. (1) At the beginning of the modeling process, modeling objects (such as processes, operations, and equipment) are determined, and the functionalities of the meta-model are defined to clarify the modeling purpose (such as decision-making, control, and diagnosis). (2) By accumulating knowledge and expertise of the modeling objects and functionalities, the meta-model is accurately expressed in various forms, such as mathematical formulas, network structures, process rules, and more. The logical interfaces (input, output, and formal parameters) used for information exchange are abstracted from the modeling objects. (3) Using multiple programming languages, the meta-model is digitally described, and software is implemented based on its functionalities and interfaces in a standardized coding fashion. (4) Based on the testing and user evaluation results, the meta-model is gradually optimized and updated through iterative improvements to increase its maturity.

Using the MODELING method, a meta-model can be described in various forms. A general meta-model with a standardized interface is formed by encoding and encapsulating various representational forms. For example, process mechanisms such as material transformation, reaction kinetics, and field phase changes in the nonferrous metallurgy process can be modeled in the form of chemical reaction equations and differential equations. Operational experience and best practices such as trend analysis and parameter setting can be modeled by expert rules, fuzzy functions, and Petri nets to create a concrete knowledge meta-model. AI methods can be represented by neural networks and tree structures.

Taking the reaction mechanism modeling of the cobalt removal process in Zn smelting as an example, the application of the MODELING method is elaborated. The reaction mechanism of the Zn smelting Co removal process was used as the modeling object to reveal the dynamic characteristics of the key indicators in the Zn smelting Co removal process over time and the operating parameters. A reaction mechanism expression form for the Zn smelting Co removal process, comprising kinetics, thermodynamics, reaction type, reaction steps, and specific reactions, was developed using prior knowledge of the Zn smelting process, material balance, production data, and physical and chemical properties, along with key process variables. The reaction kinetics and specific parameters of the Co removal process were determined using a modeling method that combined the mechanism and data. The reaction mechanism meta-model is encoded and encapsulated using software to create an industrial mechanism meta-model entity, enabling the meta-model to receive feedback updates through meta-model invocation and the application of its effects.

4 Construction technology of nonferrous metal industry intelligent model library

4.1 Intelligent model library architecture based on IIoT

IIoT serves as a fundamental network for connecting devices, materials, people, and information systems, enabling comprehensive perception, dynamic transmission, and real-time industrial data analysis to support scientific decision-making and intelligent control. This is considered a critical infrastructure for smart manufacturing [23]. In the overall architecture of the intelligent model library for the nonferrous metal industry based on the IIoT (Fig. 2), the infrastructure provided by the IIoT IaaS layer offers rich resources for the construction of the model library while collecting and aggregating data from various sources to provide “raw materials” for the development and testing of meta-models. The PaaS layer possesses scalable open cloud operating systems supported by industrial cloud middleware and microservices based on general PaaS and industrial big-data systems, providing service support for the model library in a diverse and compatible platform environment. Microservices and industrial application development tools in the SaaS layer can quickly construct customized industrial APPs, form application services that meet different scenarios, resolve practical and innovative industrial demands, and provide a convenient approach to easily invoke meta-models. The integration development platform for meta-models, comprehensive management platform, developer community, and all meta-model elements were deployed in the IIoT PaaS layer, providing core technical foundations for various industrial APP applications.

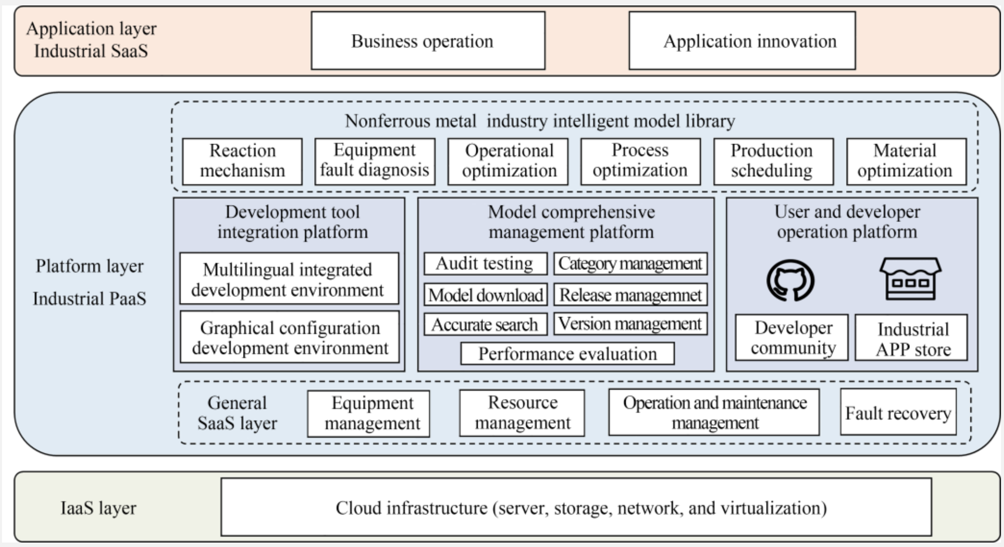

Fig. 2. Nonferrous metals industry intelligent model library architecture based on IIoT.

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The overall technical route for the nonferrous metal industry intelligent model library based on the IIoT is shown in Fig. 3. In the underlying data layer, massive amounts of production data are dynamically collected, and real-time stream calculations, extraction loading, and distributed storage are performed. Database access capability is provided through standard interfaces such as Java Database Connectivity (JDBC) and Open Database Connectivity (ODBC). For an integrated development environment, various language compilation environments and JupyterLab are adapted and integrated through technologies such as JSON-RPC, Docker, and WebSocket to build an integrated development environment that supports multiple programming languages such as C++, Java, and Python, achieving multi-language and interactive meta-model code modeling. Meanwhile, a graphical development environment was built based on technologies such as Docker, Kubernetes, and Render, achieving configuration-based operations and the atomic interaction of meta-models. Intelligent services can be rapidly developed by "drag-and-drop" connection of meta-models.

In the meta-model full lifecycle comprehensive management platform, a five-layer, two-dimensional classification system was built based on the Neo4j graph database to construct a knowledge graph of nonferrous metal meta-models. Through knowledge extraction, knowledge fusion, and semantic understanding, fast and accurate searches and intelligent recommendations of meta-models can be achieved. Digital and standardized meta-models in the model library are instantiated and encapsulated into the RESTful API to support flexible invocation methods such as curl, Python, and Scala for online use. Offline use cases are encapsulated in PMML formatted files to achieve cross-scenario usage. The "plug-and-play" meta-model invocation method enhances the industrial application development efficiency for browser/server (B/S) and client/server (C/S) architectures, improving system maintainability and flexibility in various applications.

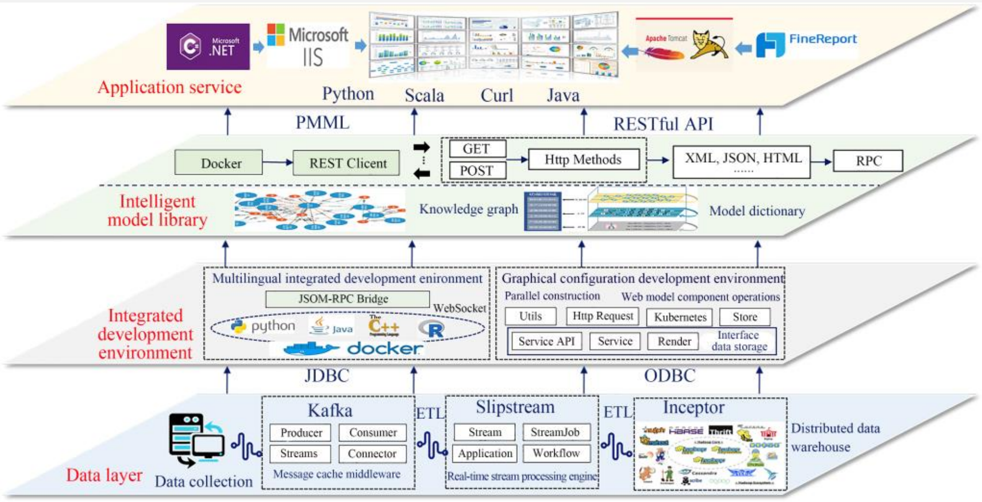

Fig. 3. Technical route of nonferrous metal industry intelligent model library based on IIoT

Note: PMML represents Predictive Model Markup Language; XML represents Extensible Markup Language; HTML represents Hypertext Markup Language; RPC represents Remote Procedure Call.

4.2 Multilingual fusion model integration agile development environment

4.2.1 Multilingual fusion meta-model integration agile development environment

Considering the differences in meta-model development languages, tools, and environments, an integrated development environment framework for meta-models with multi-language fusion is proposed. Users can freely switch compilation environments according to their needs to achieve interactive meta-model code development under multi-language collaboration. Docker technology is used at the underlying level to build virtual compilation environments for programming languages such as C++, Python, and Java. Each environment is independent of the others and adopts a parallel operation mode, eliminating coupling interference between different environments and improving the utilization efficiency of computing resources. In the front end, JupyterLab is used to adapt kernel images of various languages, and WebSocket, Bridge, JSON-RPC, and other technologies are used to complete message transmission between the front-end coding interface and the back-end compilation kernel, realizing online running of multi-language code and real-time feedback of results [24].

4.2.2 Graphical configuration model agile development environment

A graphical and configurable agile development environment was developed to reduce the threshold for model development and improve model development efficiency. The individual meta-model encapsulated in code programming was packaged as an independent image, published as standardized services, and made available for external calls. Hence, users can quickly customize the personalized models required. In the graphical and configurable interface, each meta-model is encapsulated as a “drag-and-drop” independent module through object diagrams, activity diagrams, and more. Various modules adopt hot-swap technology and can be directly selected and connected for calling. Users can drag the modules to select the required meta-models and connect input/output relationships based on the logical relationship of the meta-models in the application, quickly completing the model development in a visual configuration form. During execution, meta-models transmit the data flow according to the logical relationship of the connection, sequentially calling the corresponding services that are connected to the underlying operator image. When a meta-model is called, a calculation task is issued to the underlying image through a service. After completion of the calculation, the result is uploaded to the graphical interface and passed on to the next meta-model. Specifically, when a meta-model task is completed, multiple meta-models directly connected to it can be executed in parallel, significantly improving the computational efficiency.

In the graphical and configurable agile development environment for models, users use knowledge associations and logical strategies to perform graphical “drag and drop” and directional connections on meta-models based on existing basic meta-models. Sentence-level programming is converted into component assembly, quickly completing the development of different models and achieving programming with reusable features. The “process is the code” form largely avoids the shortcomings of computer programming skills among personnel in the nonferrous metallurgy industry, enabling them to leverage their professional advantages and lower the threshold and cost of model development.

4.3 Encapsulation method for nonferrous metallurgical meta-model

After the meta-model is encoded and the interface is defined, it must be encapsulated into an object-oriented model for modular storage management and standardized and convenient calling. This hides the details inside the entity (providing access interfaces only to the outside), allowing users to make direct calls without knowing the specific implementation process of the function. Standardized and modular methods simplify application programming, improving meta-model management and application efficiency, enhancing system maintainability, and protecting the intellectual property rights of meta-model developers. From the perspective of the full lifecycle of the meta-model definition and development, management, and application, meta-model encapsulation must meet requirements such as reusability, interoperability, cross-platform, standardization, interface compatibility, and security.

The proposed encapsulation architecture for the nonferrous metallurgy meta-model (Fig. 4) defines clear inputs, outputs, and parameters, enabling a prototype of the meta-model with modeled codes and interfaces. The meta-model properties and proxies are then obtained through standardized encapsulation. The meta-model properties include the number, name, function, interface, and programming language, which describe meta-model-related information and provide a basis for meta-model management and invocation. The meta-model proxy serves as a reference for the meta-model prototype, exposing only the input/output interfaces and limited parameters to the outside. Users do not need to access the meta-model prototype but can call it through the proxy. The proxy pattern protects the meta-model prototype from arbitrary modifications to its code or methods while allowing users to freely add additional functionality on top of the meta-model proxy, enhancing its scalability.

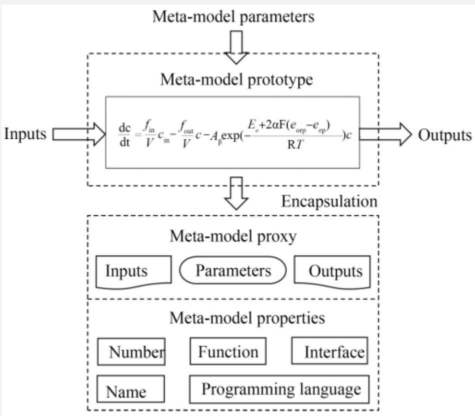

Fig. 4. Nonferrous metallurgy meta-model encapsulation architecture.

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During meta-model invocation, significant differences may arise in deployment environments and methods. For example, a meta-model can be encapsulated and released for internal platform deployment, allowing online calls within the same network environment. Alternatively, it can be published in the cloud and invoked on the edge, supporting online invocation through network interconnections. In addition, owing to network restrictions in different enterprises or regions within the same enterprise, effective bidirectional communication cannot be achieved between the meta-model publishing and calling ends; hence, the meta-model can only be transmitted offline to the calling end for deployment. Considering the differences in meta-model deployment environments and the proprietary requirements of meta-model encapsulation, an encapsulation method for a nonferrous metallurgy meta-model was proposed for both online and offline calling. The meta-model proxy constructed in the form of the RESTful application programming interface (API) and PMML provides online and offline encapsulation of the meta-model, respectively, with good independence, generality, reusability, compatibility, and support for a unified description of heterogeneous languages and cross-platform invocation.

For online invocation: after the meta-model is developed on a cloud platform through code editing and interface definition, it is encapsulated as a meta-model proxy in the form of a RESTful API and published externally. The RESTful API primarily includes a uniform resource locator (URL) for the connection and a token for authentication [25]. After obtaining a token, users can authenticate the URL to obtain usage rights. Users can obtain the output results of the meta-model by accessing the input data and parameters of the calling templates. Based on the concept of runtime black-box reuse, the RESTful API provides external access to the meta-model ontology in the form of URL links, shielding users from internal implementation details and retaining interfaces and limited parameters, thereby avoiding the impact on the meta-model prototype. In addition, there are no special requirements for the user's programming language or resource environment, and there is no need to modify or configure the deployment environment. The openness of the interface enables flexible cross-platform calling, and the structured message format presents inputs/outputs in a standard format, endowing the meta-model with interoperability through standardized and open interfaces.

For offline invocation, the meta-model can be encapsulated in the PMML format and pushed offline to the user as a file [26]. After obtaining the meta-model proxy PMML file, the user can use standard loading and calling methods in programming languages such as Python or Java. The PMML relies on a meta-model generated using a unified XML format. The target environment can parse the PMML library to load the meta-model. They can be operated on different operating systems and application platforms with good independence and portability.

4.4 Meta-model full lifecycle comprehensive management platform

The meta-model's full lifecycle comprehensive management platform includes quality audit and testing, classification management, release management, version management, precise search, model downloading, and performance evaluation. (1) Quality audit and testing: Meta-models uploaded by developers are tested from professional perspectives, such as functionality and reliability. After passing an audit, the meta-models can be stored in a model library for the user. (2) Classification management: A multi-dimensional classification system is established for numerous meta-models, and tags are assigned to the meta-models for classification management. (3) Release management: Resources such as computation and memory are reasonably allocated to meta-models, which are selectively put online for use. (4) Version management: Considering the iterative updates of meta-models during use, the released meta-models are continuously upgraded, and new images are constructed while preserving historical images. (5) Precise search: Users can select meta-models based on their requirements and filter them using category tags. Moreover, they can conduct keyword searches to obtain the required meta-models quickly. (6) Model downloading: Meta-models can be downloaded as a RESTful API or PMML according to online and offline use requirements. (7) Performance evaluation: Users can rate the meta-models based on their experiences and provide descriptive comments. Continuous user feedback helps optimize the meta-model quality. This study focuses on research and progress in classification, audit, evaluation, and search, emphasizing key content related to these aspects.

4.4.1 Classification system of the nonferrous metallurgy meta-model

In the nonferrous metallurgy process industry, the process hierarchy can be divided into the entire process, process, and equipment layers. There are many coupling relationships between each process, and meta-models can be nested with each other. By cascading multiple meta-models, new models can be derived; for example an entire process model can be obtained through a cascade of multiple process meta-models and a process model can be obtained through a cascade of multiple equipment meta-models. In addition, all meta-models in each layer have corresponding functions, such as production optimization control, material formula optimization, operation status monitoring, and other main functional domains, each of which includes specific functional properties. Based on this, a multi-dimensional classification system for the meta-models of nonferrous metallurgy is proposed and comprises the layers of whole process, unit process, equipment, functional domain, and functional label" (Fig. 5).

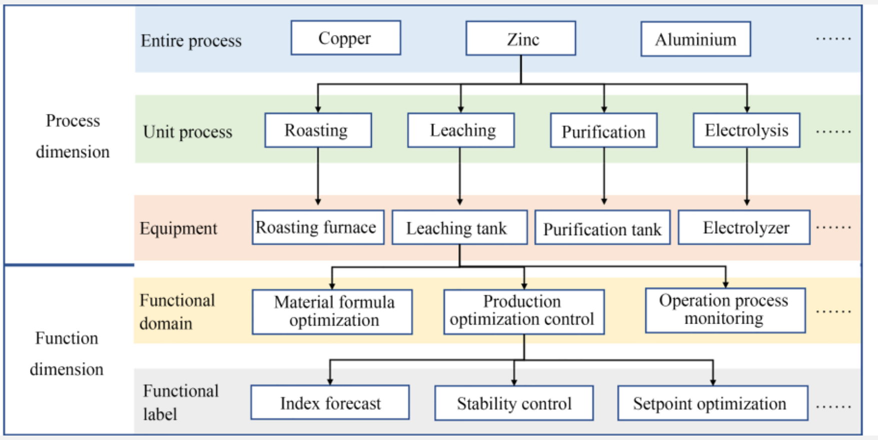

Fig. 5. Nonferrous metallurgy meta-model classification system.

The "five-layer, two-dimensional" meta-model classification system is mainly divided into process and function dimensions: the former is divided into three levels of overall process, unit process, and equipment from top to bottom, according to the physical structure of different metal types and smelting processes. The latter includes two levels of functional domain and functional label, which describe the functional characteristics of the meta-model from macro categories and micro attributes. For example, the meta-model for predicting the soluble zinc content of zinc roasting concentrate belongs to the overall process of zinc smelting–roasting process–roasting furnace equipment; by inputting the standard temperature and zinc concentrate assay value, the soluble zinc content of zinc roasting concentrate can be predicted, and the optimization of the standard temperature setting value can be guided. Hence, in the function dimension, it belongs to production optimization control-indicator prediction. Through a standardized and structured classification system, meta-models with the same properties or features are collected, and the resulting clear and hierarchical architecture facilitates meta-model queries, identification, management, and invocation.

4.4.2 Review and evaluation system for nonferrous metallurgical meta-models

The quality of the nonferrous metal industry intelligent model library was determined by the quality of the meta-models. From the developers' perspective, functional and reliability reviews of meta-models are required, and only meta-models that have undergone testing can be added to the model library for use. The maturity and operational efficiency of the meta-models are evaluated from the users' perspective, and iterative improvements of the meta-models are performed based on user experience.

Developers submit meta-model source code, user manuals, and requirement specifications, which are judged and tested by system administrators and industry experts based on formal standards, functionality/performance, and other aspects. The meta-model can only be stored in the model library when the overall indicator and specific item scores meet the audit standards. The multi-dimensional audit system ensures model quality at the source, and the relevant audit indicators include functionality, reliability, robustness, security, ease of use, and execution efficiency. Functionality is evaluated by completeness and correctness assessments. Reliability describes the ability of meta-models to complete a specified function within defined time and conditions and can be measured by the mean time between failures. Robustness is qualitatively described by fault tolerance and recovery capabilities. Security refers to the ability of a meta-model to run correctly and ensure that the software runs legally within the authorized scope when facing malicious attacks. Ease of use refers to the ease of understanding, learning, and operation of the meta-model inputs/outputs and parameters during use. Execution efficiency is quantitatively described by the time characteristics and resource features under multiple service concurrency conditions.

Only users with experience with the meta-model can evaluate it; this evaluation is divided into user ratings and comments. The former includes functionality completeness, correctness, stability, fault tolerance, and ease of use; users rate each dimension numerically. The latter serves as a qualitative evaluation and can directly express user opinions of the model (such as usage experience and improvement suggestions). User feedback directly reflects the

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actual performance of the meta-model in the application stage, and developers can iterate and optimize the meta-model based on the evaluation feedback.

4.4.3 Meta-model search engine based on domain knowledge graph

The interrelationships among the nonferrous metallurgy meta-models are strong. As the number of meta-models increases, the complexity of the relationship between them increases exponentially. Traditional relational databases have long search times and high resource loads, making it difficult to meet the fast search requirements of a large number of nonferrous metallurgy meta-models. A knowledge graph is a semantic network that reveals relationships between entities. A clear and explicit relationship network supports the fast retrieval of results. Building a meta-model search engine can achieve the efficient retrieval and management of meta-models, improving their application efficiency.

Constructing a knowledge graph in nonferrous metallurgy consists of five parts: ontology design, knowledge extraction, knowledge mapping, knowledge fusion, and knowledge storage. (1) Ontology design. This is based on the experience of industry experts in constructing an ontology in a top-down manner. The inputs include knowledge, terminology dictionaries, and expert experience in nonferrous metallurgy, whereas the outputs include entity categories constituting the knowledge graph and the relationships between categories. The 7-step method [27] is commonly used to mine knowledge in the field of nonferrous metallurgy, define the concept ontology of meta-models, and form a nonferrous metallurgy meta-model ontology library (Fig. 6). (2) Extracting knowledge. Knowledge graph nodes are constructed by extracting entities, properties, and the mutual relationships between entities from diverse data sources. Based on rule-based methods, entity identification and relationship extraction are conducted, establishing a knowledge library as “entity–relationship–entity” triplets and forming ontology-based knowledge expression. (3) Knowledge mapping. Organizing the extracted entities, properties, and relationships according to the ontology design allows the formation of nodes and facilitates a unified internal knowledge representation. This, in turn, enables multi-source knowledge fusion and inference in knowledge graph applications. (4) The fusion of knowledge involves integrating new knowledge, eliminating contradictions and ambiguities, and fusing various types of knowledge using methods such as referent resolution, entity disambiguation, and entity linking (5) Knowledge storage. Graph databases, as non-relational databases, are adopted to store entity-entity relationships, nodes, edges, properties, and other essential composition elements corresponding to entities, relationships, and properties in the knowledge components. Using the Neo4j graph database [28] as a medium completes the knowledge storage, significantly improving the efficiency of association queries.

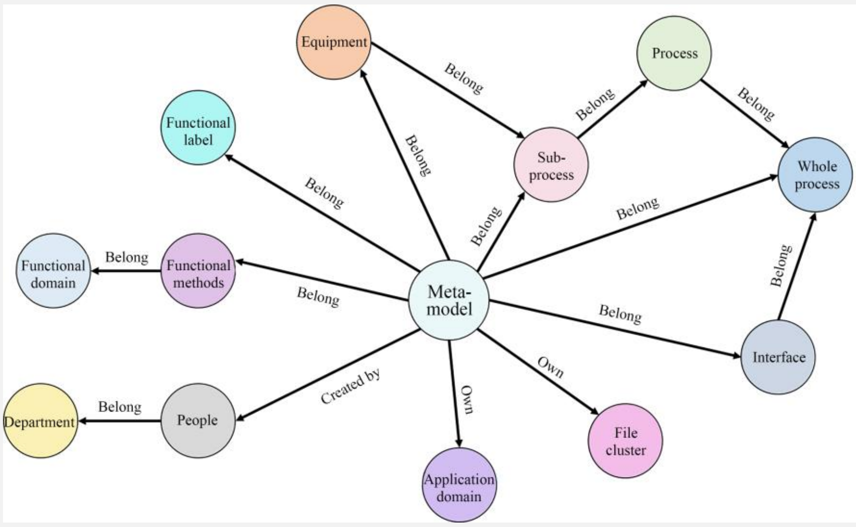

Fig. 6. Nonferrous metallurgy meta-model ontology library.

The meta-model search process based on the domain knowledge graph is as follows: (1) For the selected labels or query text input by the user, semantic understanding is used to extract attributes and relationships from the labels or query text. (2) Based on the Cypher querying language of the Neo4j graph database, a database querying statement is automatically generated using the relevant attributes and relationships. (3) The meta-model number in the knowledge graph is searched according to the query statement, and the corresponding meta-model is obtained by indexing the library, thereby returning the search results. The main methods used by users to search for the required meta-models are label selection and keyword search. The former mainly relies on the classification query of model-related nodes; that is, starting from the meta-model ontology node and ending at the function domain and function label nodes selected by users, all meta-model nodes pointing to the label node are retrieved using the Cypher querying language. In the Cypher querying language, the keywords of the meta-model properties are automatically converted into querying conditions in the Match querying statement, and the meta-model nodes that satisfy the querying conditions are then retrieved as output.

5 Nonferrous metal industry intelligent model library and application

5.1 Nonferrous metal industry intelligent model library

Based on the aforementioned technology, we successfully built a nonferrous metal industry intelligent model library with an IIoT architecture. The library uses a multi-language integrated meta-model agile development environment to retain the nonferrous metallurgical process mechanisms, experiential knowledge, data models, and AI methods (Fig. 7). The physical, operational environment of an intelligent model library is equipped with high-performance central processors, storage systems, and graphics processors to meet the requirements of meta-model development, testing, operation, release, and management.

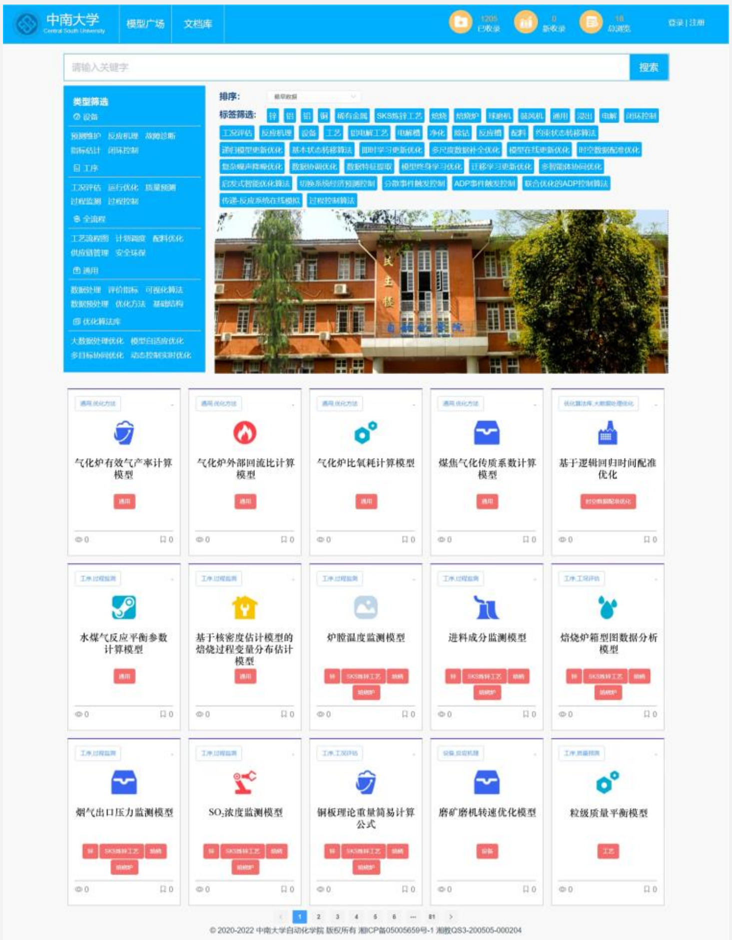

Fig. 7. Nonferrous metal industry intelligent model library.

The nonferrous metal industry intelligent model library focuses on the production processes of copper, aluminum, lead, zinc, and other nonferrous metals. It covers 25 subclasses under five main categories: equipment, process, entire process, general, and optimization algorithms. Currently, 1251 meta-models are available from this library. To address the urgent need for nonferrous metallurgical production, such as intelligent equipment monitoring and raw material supply chain optimization, solutions have been developed and applied in key nonferrous metallurgical enterprises. This effectively improves the industry intelligence level and creates significant economic benefits.

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5.2 Application 1: intelligent monitoring of zinc roasting furnace

A roasting furnace is a large-scale equipment used in the Zn smelting process, and its operating status is crucial not only for the stable operation of downstream processes but the entire process [29]. Condition identification and operational optimization are vital to ensuring the long-term safety, stability, and efficient operation of roasting furnaces. Owing to the large volume, complex structure, strong coupling of subsystems, and serious imbalance between multiple-sampling-rate operating data and assay data, monitoring and controlling the operational status of the related equipment is difficult. Under the current manual operation and maintenance service mode, the equipment operation efficiency is low, abnormal states are frequent, and temperature fluctuations are large; hence, long-term stable operation is difficult.

To address this engineering challenge, several applications that utilize meta-models from the model library have been developed. These applications include the fluidization velocity calculation model, fault identification model, temperature setting model, operating condition classification model, reconstruction error control limit calculation model, and error-triggered update model for roasting furnaces. Together, they constitute an intelligent monitoring solution for the zinc smelting roasting furnace, enabling functions like autonomous evaluation of operational status, multilevel equipment fault diagnosis, and temperature-stable control. For example, in the temperature real-time stable control of the roasting furnace, various meta-models such as the total sensible heat of the feed, flue gas sensible heat, feed rate control under the mechanism model, temperature trend extraction and analysis, and fuzzy rule control algorithm are interconnected using a “drag-and-drop” approach. This facilitates the rapid creation of a mechanism and data-driven temperature real-time stable control model for the roasting furnace, based on the specific business logic. The application service is encapsulated and published in the RESTful API and can call applications under various architectures, such as B/S and C/S. In addition to configuring meta-models to build model services, various RESTful APIs or PMML application systems provide individual meta-models for calling.

Based on the meta-models related to intelligent monitoring of the zinc smelting-roasting furnace, a solution including a series of applications has been constructed, and engineering applications have been conducted in lead-zinc smelting enterprises (Fig. 8). This significantly reduces the production failure rate of the roasting furnace, improves the temperature control accuracy, and achieves long-term stable operation.

Fig. 8. Intelligent monitoring solution for zinc roasting furnace.

5.3 Application 2: raw material supply chain optimization in zinc smelting enterprises

Zinc concentrate is an important raw material in the zinc smelting process, and its procurement and coordination directly affect the production and operation of enterprises. However, the annual procurement cost of zinc concentrate is several billion CNY, accounting for approximately 70% of the total cost, with a high capital utilization rate [30]. Reducing procurement costs by 1% increases the profit of the enterprise by 5%–10%. However, Zn smelting is a continuous production process, and a continuous supply of raw materials is required because of the high cost of material interruption recovery. As the first step in the Zn smelting process, the quality of raw material blending directly affects the stability of subsequent production processes and product quality. The combination of raw material price fluctuations, varying supplier quality, subjective manual decision-making, and lack of proper feedback on information often results in issues such as high inventory occupation, elevated procurement costs, and an influx of impurities in raw materials.

To address the issues in the raw material supply chain, a solution for the raw material supply chain was constructed based on relevant meta-models in the intelligent model library (Fig. 9). The meta-models used included the metal balance, safety stock setting for zinc concentrate, multi-dimensional evaluation of zinc concentrate suppliers, multi-metal comprehensive pricing of zinc concentrate, and order allocation of zinc concentrate. After applying the solution to the raw material supply chain, a fully integrated optimization from raw material procurement to material blending was achieved, significantly improving the quality of material supply and blending and the stability and efficiency of subsequent production processes, thereby improving the enterprise's production costs.

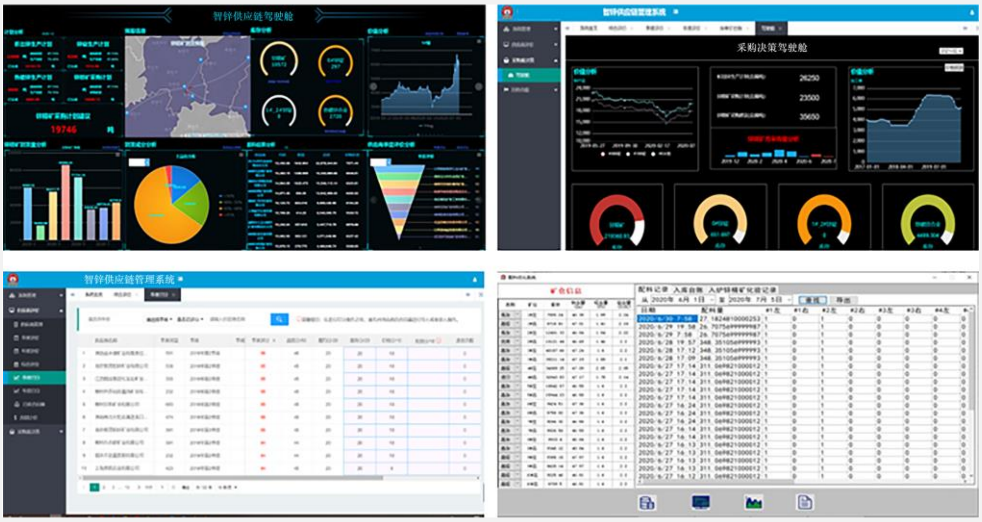

Fig. 9. Raw material supply chain optimization solution.

6 Conclusion

The nonferrous metal industry plays an important role in China's economic and social development, and industrial software is an innovative driving force for the high-quality development of the nonferrous metal industry. This study addresses the practical challenges in developing and utilizing nonferrous metal industry models. It proposes a theoretical system for nonferrous metallurgy meta-model modeling and encapsulation, an architecture for a nonferrous metal industry intelligent model library based IIoT, and establishes a multi-language model agile development environment and a comprehensive meta-model lifecycle management system. Typical scenarios in nonferrous metallurgy show that the intelligent model library is crucial for improving the level of industrial intelligence in practical applications, providing innovative technological support for the construction of a strong country in the nonferrous metal industry.

Knowledge of the nonferrous metal industry is complex and diverse, and the production process is dynamic and changeable. In the future, knowledge discovery and model self-learning should be explored in depth. (1) In-depth mining and explicit representation of tacit knowledge. Explicit knowledge, such as the process mechanism and intelligent methods of nonferrous metallurgy, can be relatively easily precipitated into meta-models; however, tacit knowledge, such as the know-how and intuition of knowledge workers, is difficult to obtain accurately, and the relevant content needs further research. (2) Adaptive online updating of models in complex dynamic environments. Most existing models have fixed structures that are unsuitable for complex, changeable, dynamic, and uncertain nonferrous metal production processes. Therefore, it is necessary to study model-adaptive online updating methods and establish a self-consistent and autonomous software system through model self-learning. Research breakthroughs on related issues will further enhance the intelligence level of nonferrous metal industry model libraries and promote the steady development of new technologies, thinking, and formats.

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